AIAA Aviation

Overview of Uncertainty Analysis Activities at NASA Glenn's Aeropropulsion Facilities

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Overview

- Background
- Objectives
- Approach
  - Uncertainty Classification
  - Defining elementary errors
    - Instrumentation
    - Random
    - Systematic
  - Monte Carlo Simulation

Why? And Why Now?

- As technology progresses, the changes on the variables of interest get smaller. Researchers need to know that the change of interest (for example, 1% increase in thermodynamic efficiency) are measureable and not within the uncertainty of the measurement.
- The uncertainty of the operating condition of the facility directly impacts the uncertainty of the measured variable.

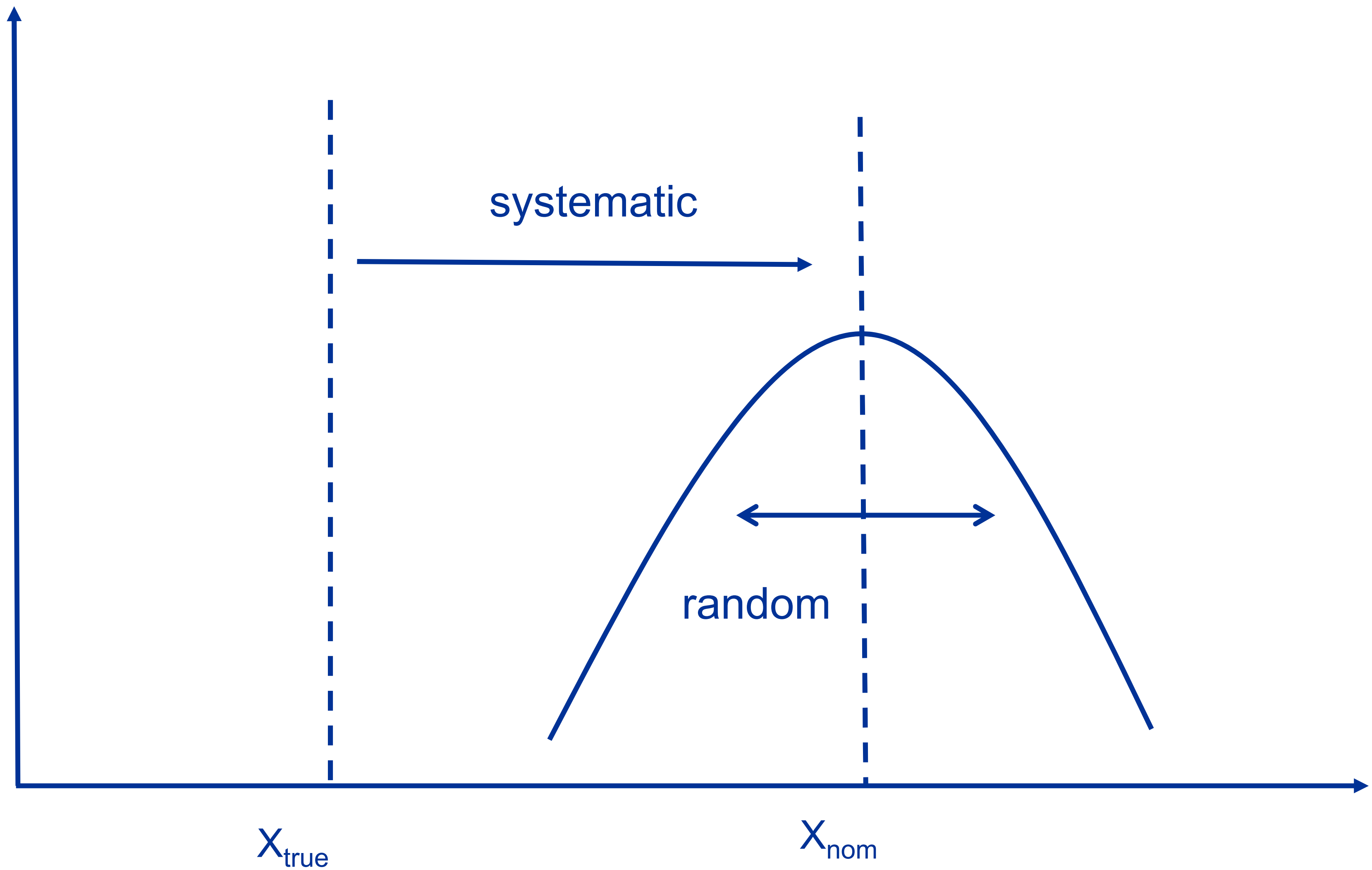
Objectives

- Develop Measurement Uncertainty Analysis Knowledge in the GRC Testing Division
- Develop a tool to analyze Instrumentation Level uncertainties in all facilities
- Determine Facility characteristic uncertainties for all aeropropulsion test facilities at GRC
- Train all GRC Testing Division Staff in the uncertainty analysis process

Approach

- Determine the variable(s) of interest
- Determine the uncertainty sources
- Determine a usable data set
- Define a model
- Analyze

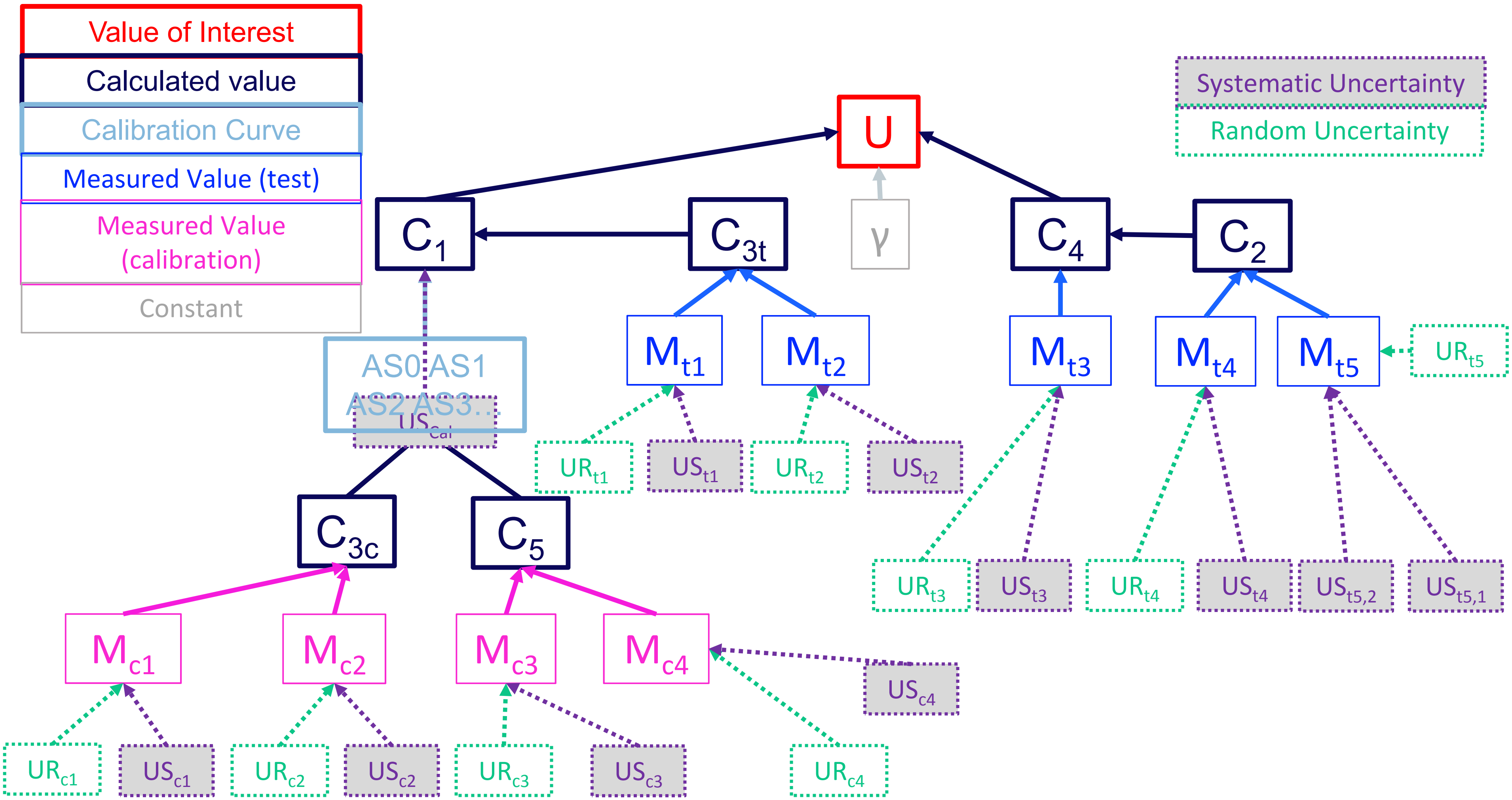
Random Vs. Systematic



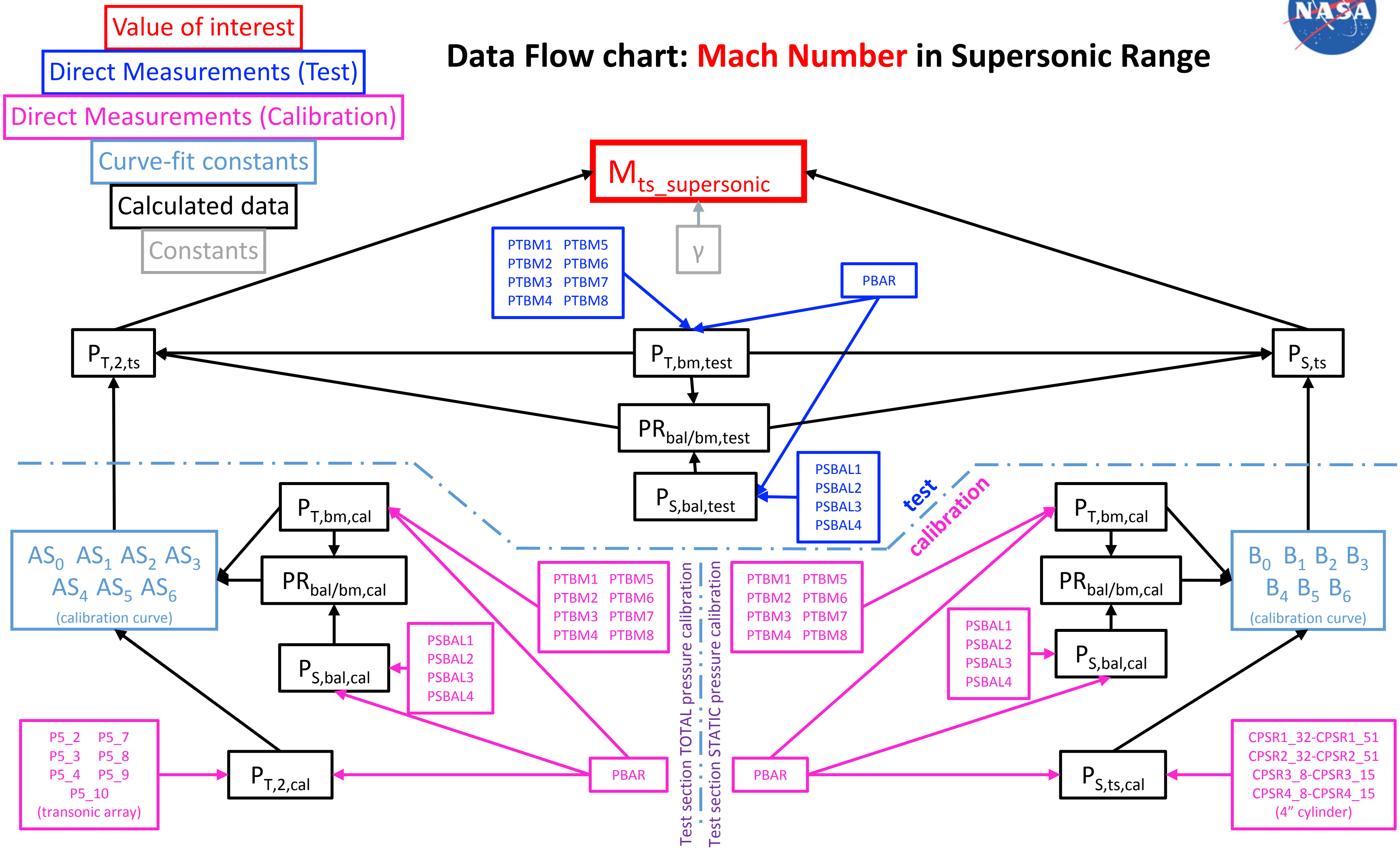
Uncertainty Type Classification

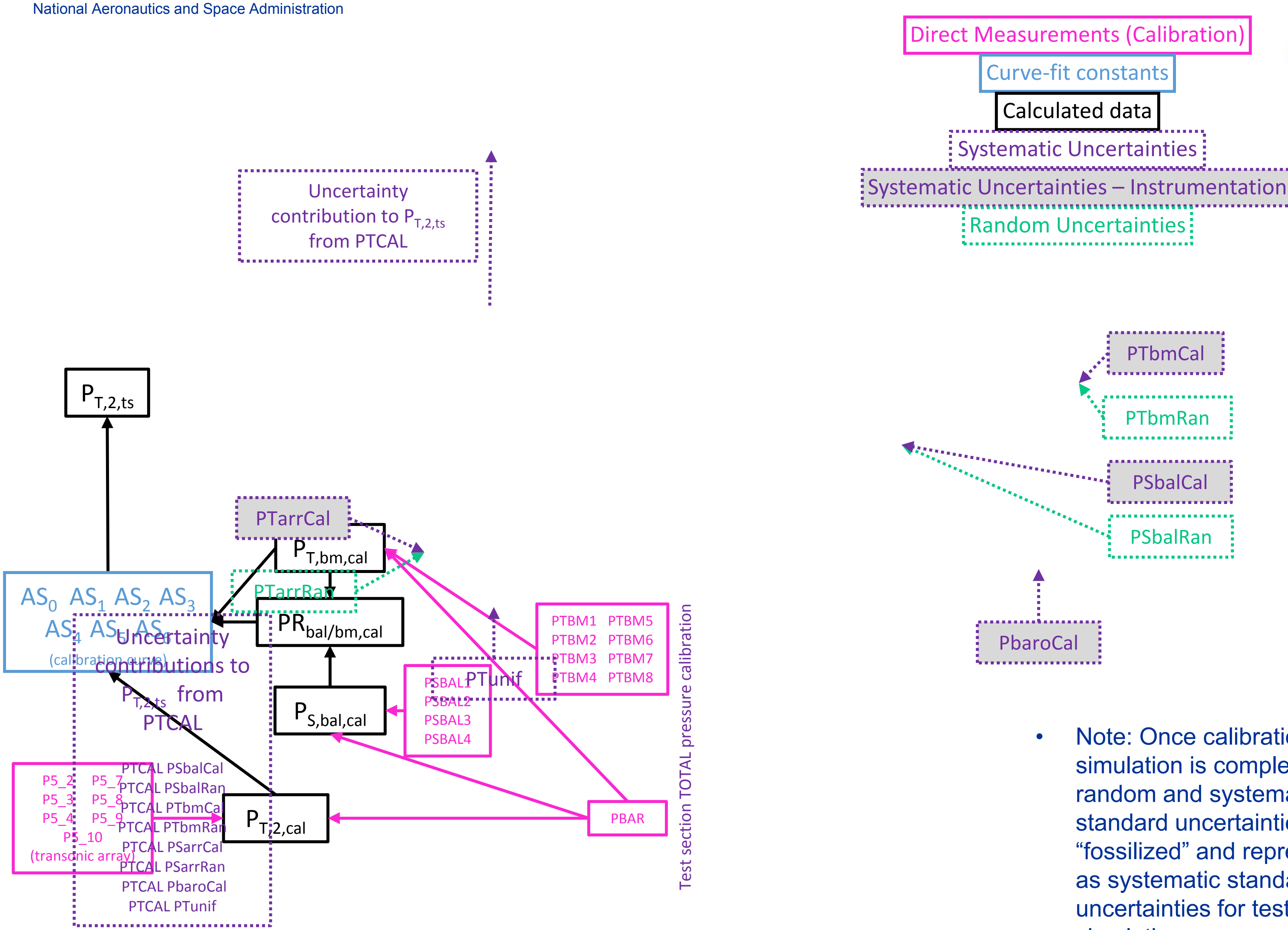
- ISO GUM:
  - Type A: evaluate by statistical analysis of observations (calculated with a standard deviation)
  - Type B: evaluate by other means (based on calibration certificates, past experience, etc.)
  - No distinction between "random" and "systematic" to avoid ambiguity
- Distinguishing between Random and Systematic is useful in determining changes that will improve facility uncertainty.
  - comparison with CFD results cares more about systematic uncertainty
  - tests looking at the effect of model changes will care more about random uncertainty.

Uncertainty Propagation



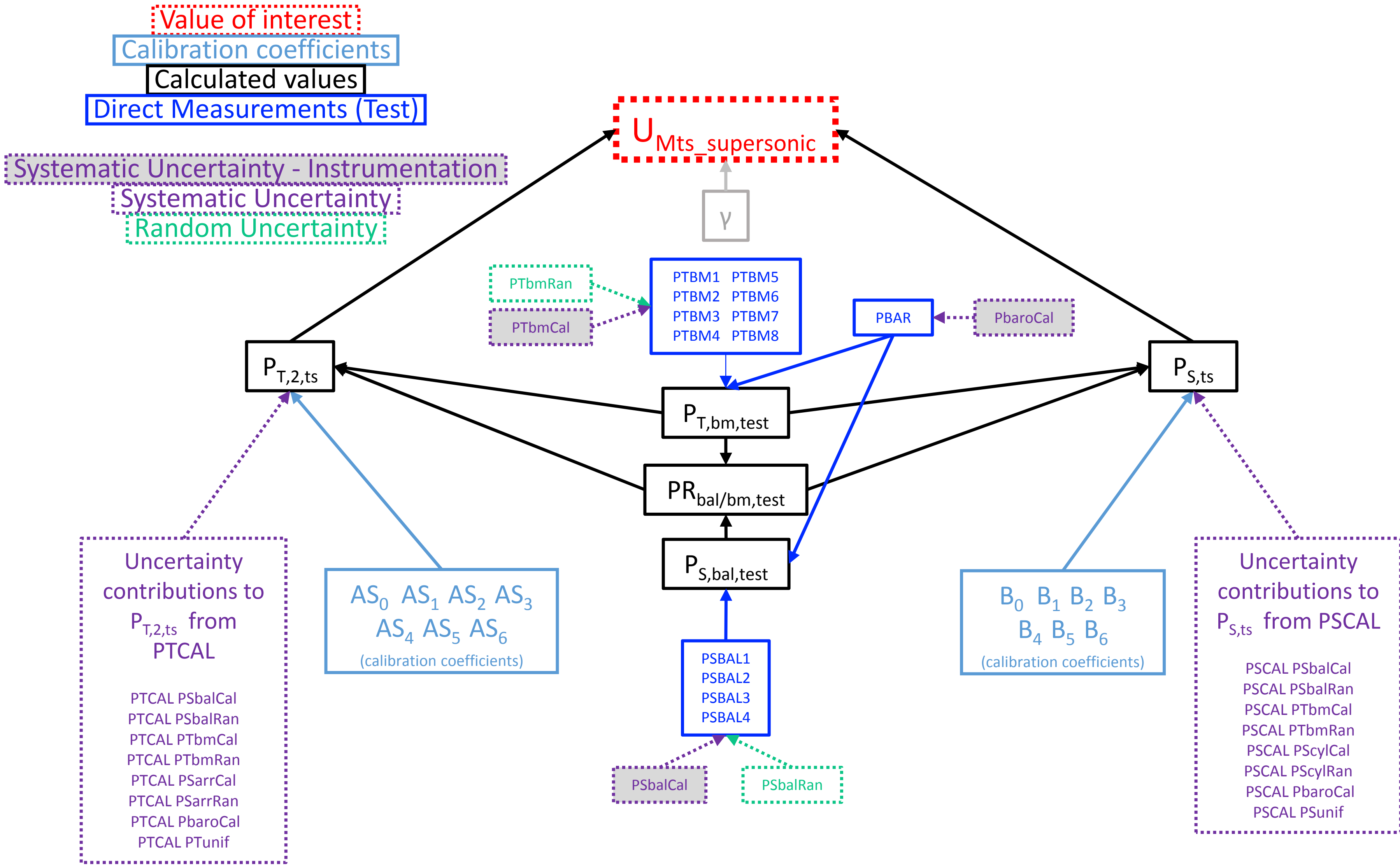
Data Flow chart: Mach Number in Supersonic Range





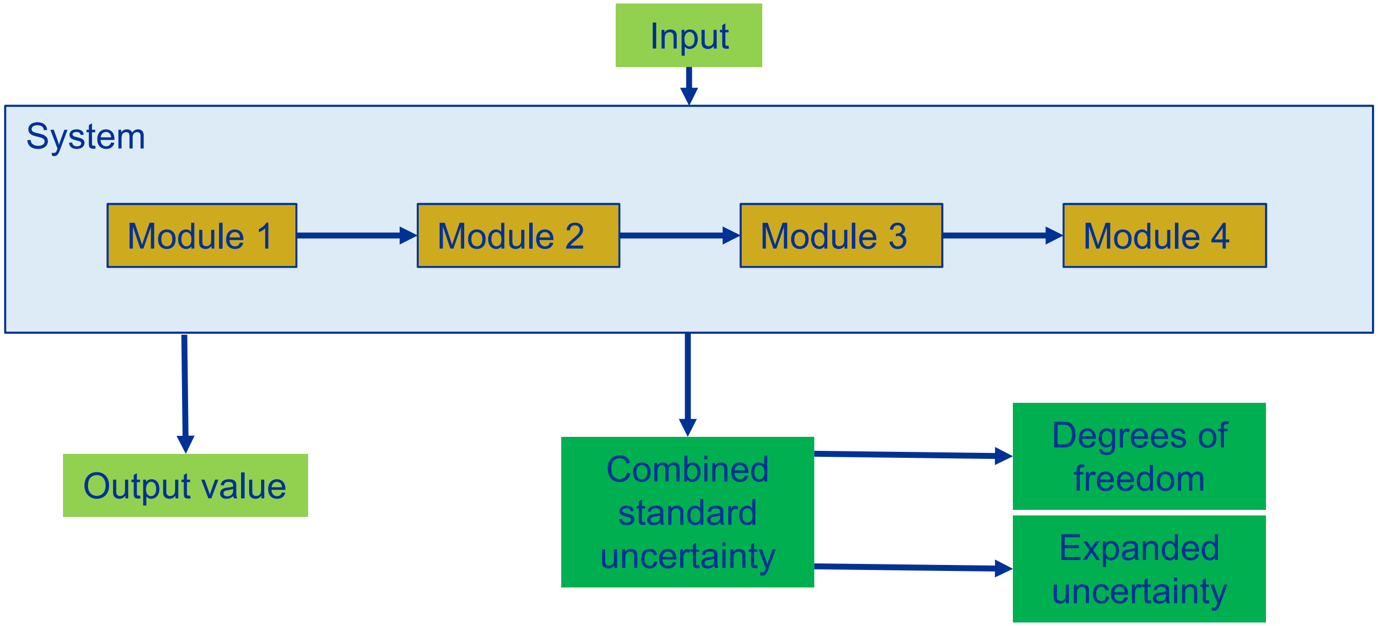
- Note: Once calibration simulation is complete, both random and systematic standard uncertainties are “fossilized” and represented as systematic standard uncertainties for test simulation

Uncertainty Propagation chart: Mach Number in Supersonic Range



Elemental Errors: Instrumentation Uncertainties

- Spreadsheet based
- ISO Guide to the Expression of Uncertainty in Measurement (GUM)*



*JCGM 100:2008 Evaluation of Measurement Data – Guide to the Expression of Uncertainty in Measurement

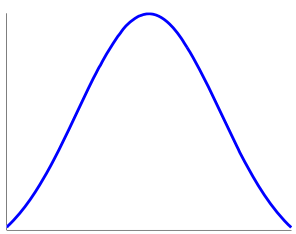
Elemental Errors: Random Uncertainties

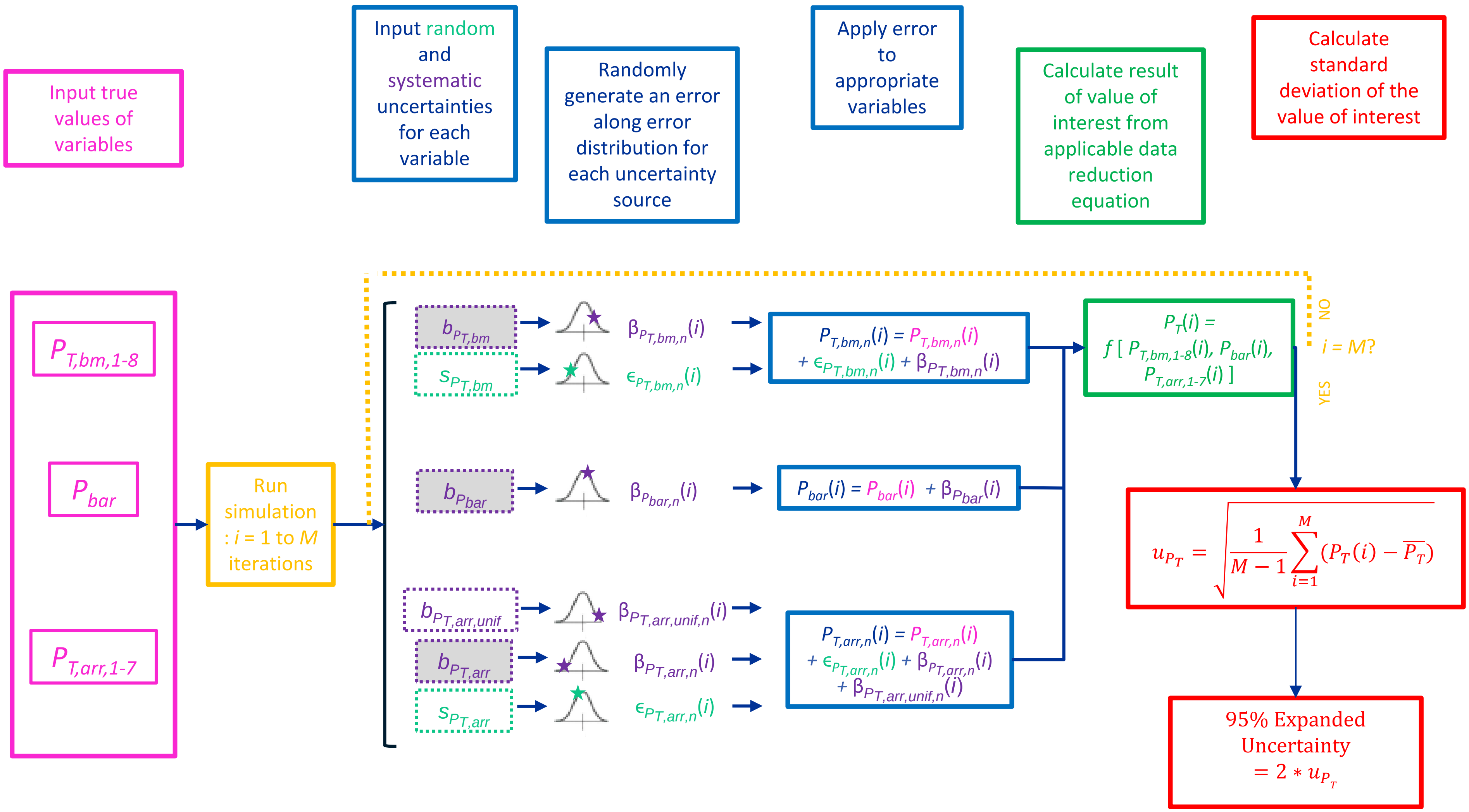
- Random deviation about the measured value
- Mean Value:

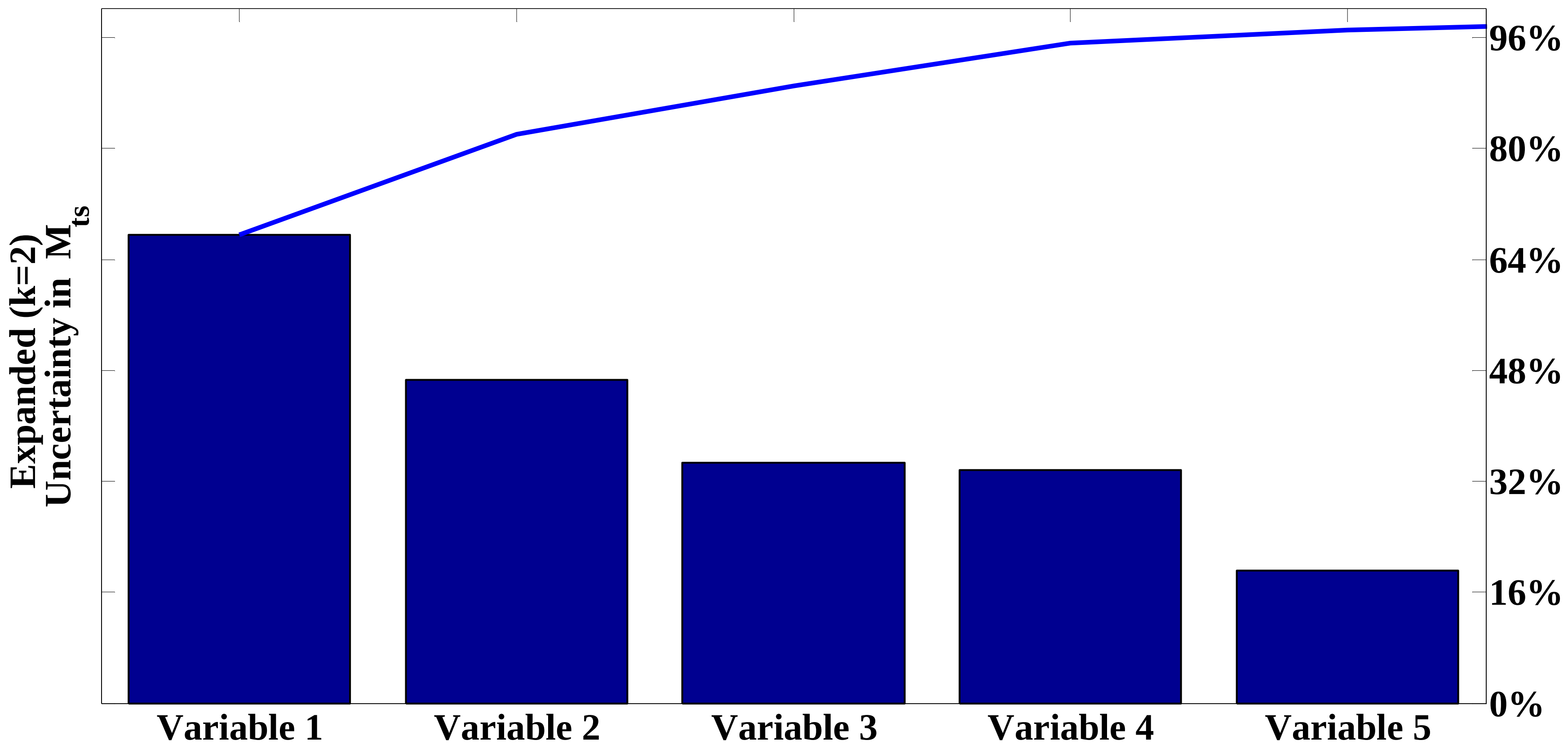
$$\overline{X} = \frac{1}{N}\sum_{i=1}^{N} X_i$$

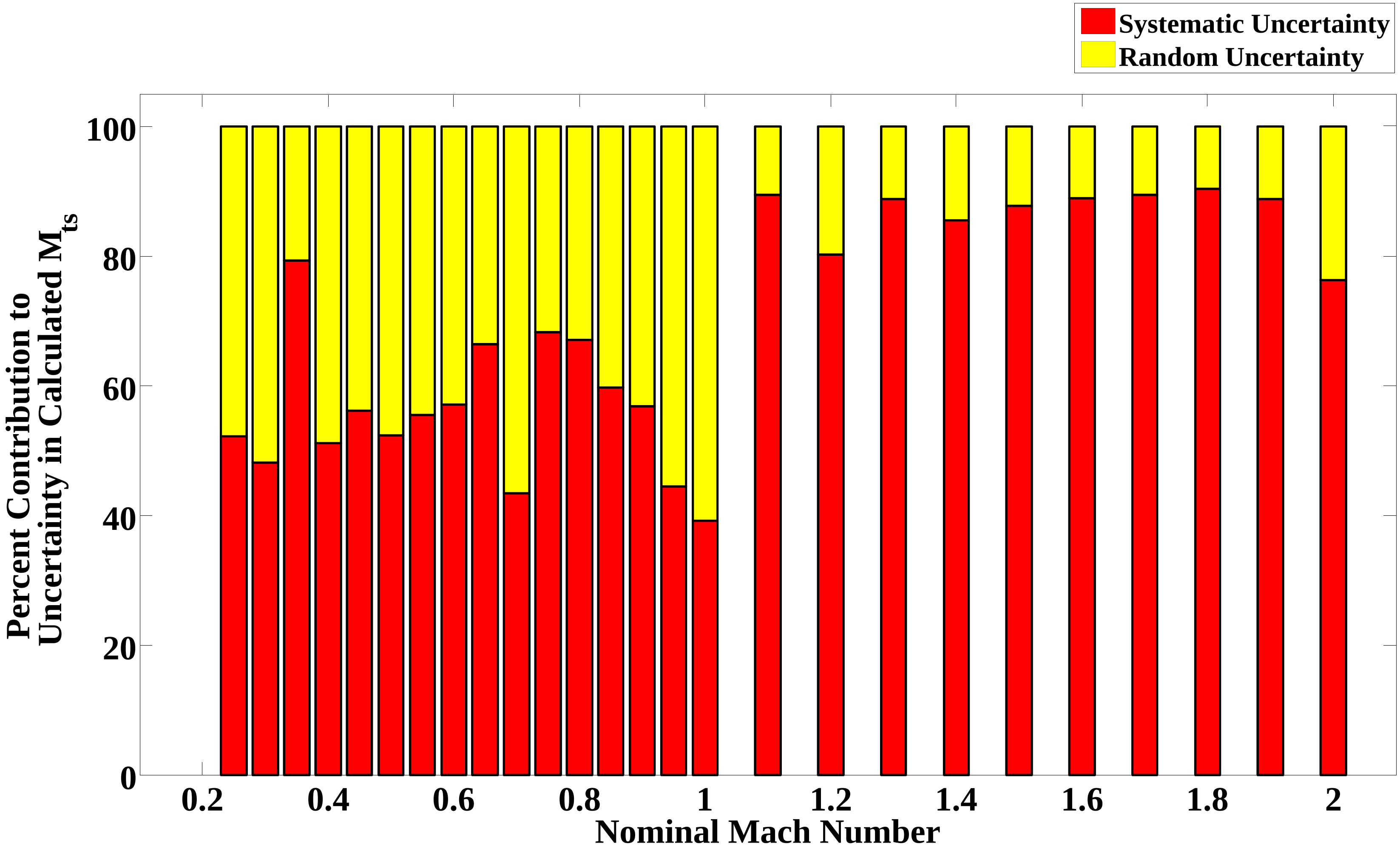
- Standard deviation:

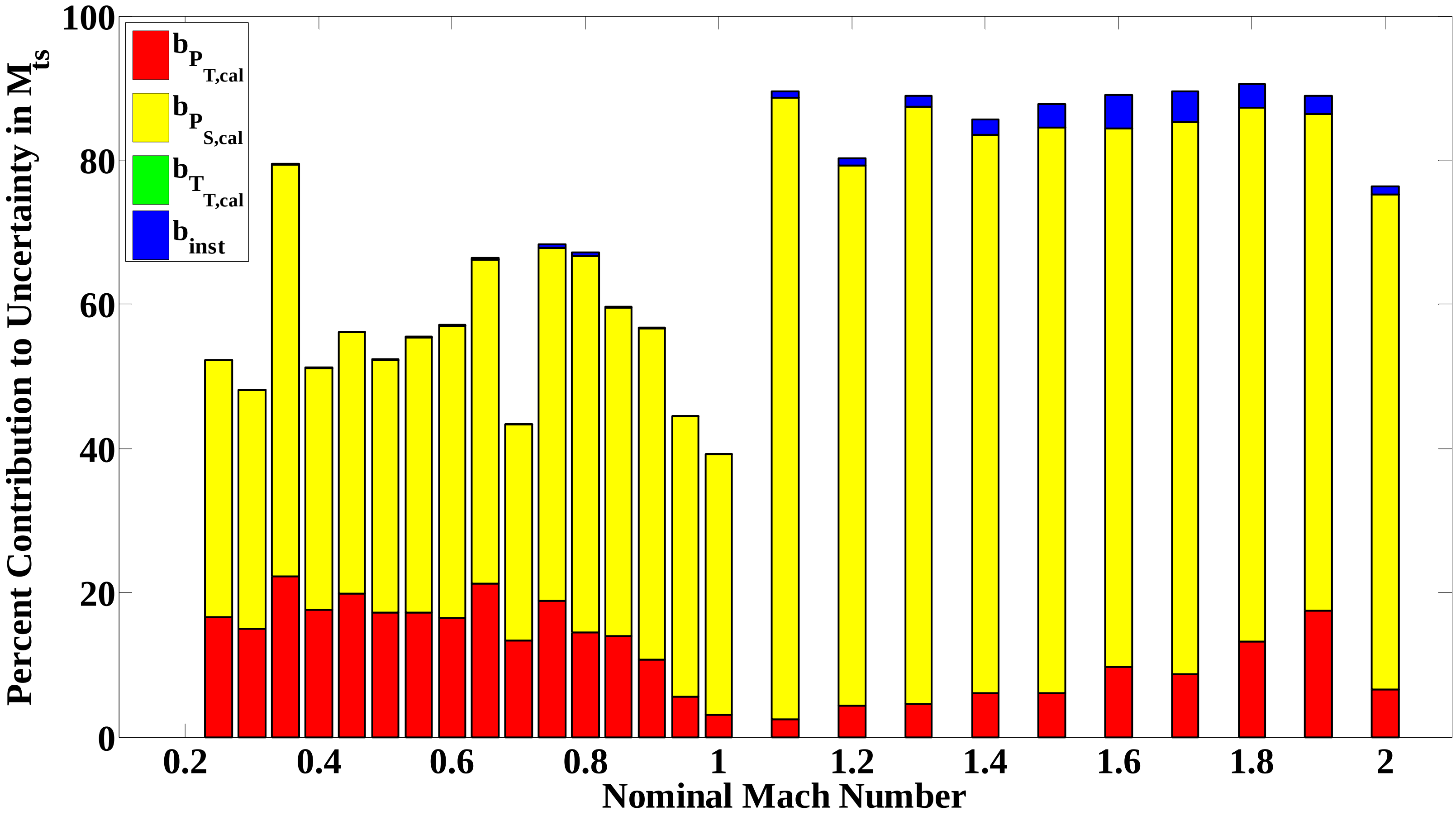
$$\sigma_X = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(X_i - \bar{X})^2}$$

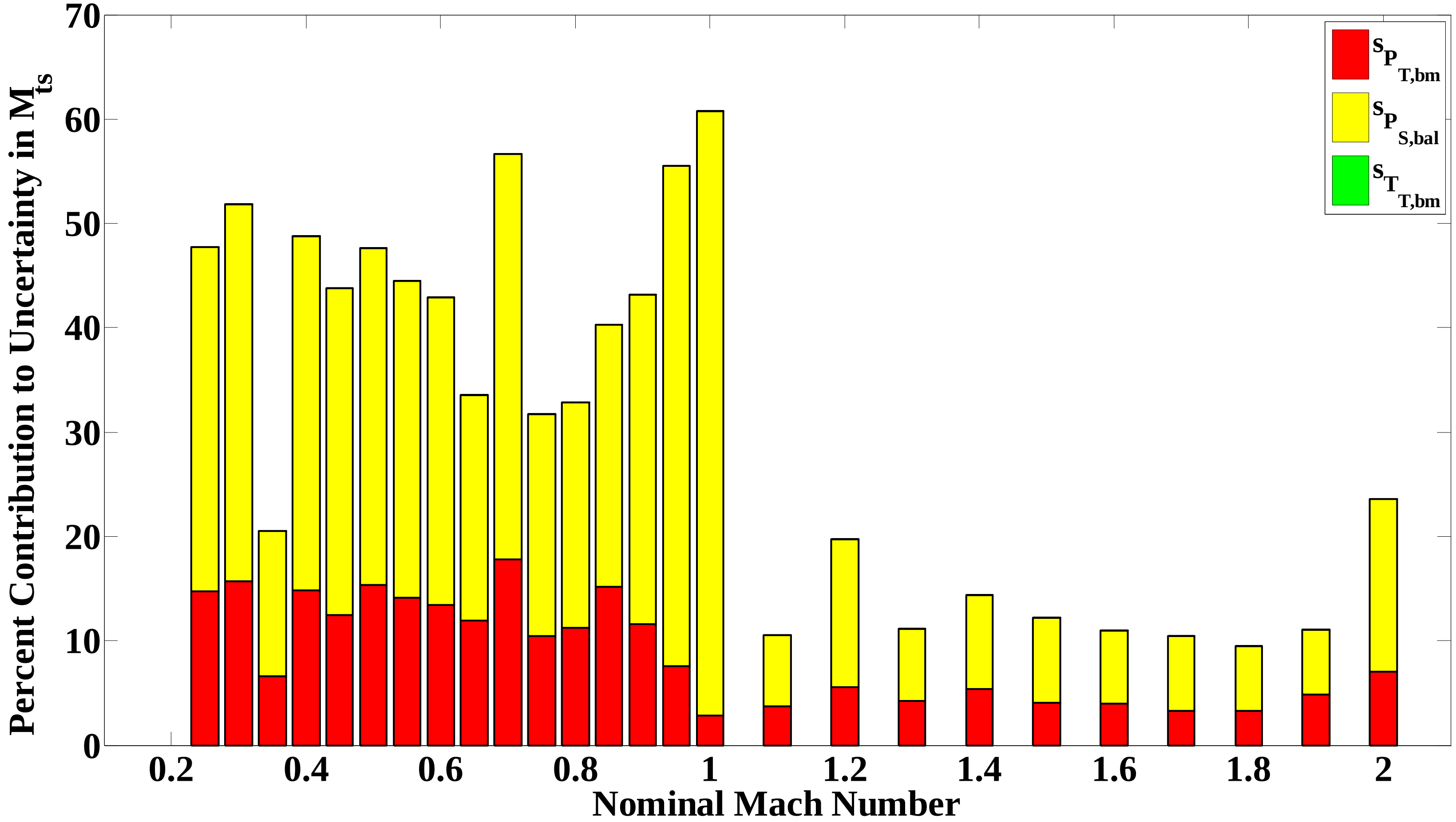
Random number	Scaled by	uncertainty			error
 $R_{r,p,i}$	×	random	s	=	$\epsilon_{r,p,i}$
$R_{p,i}$		systematic	b		$\beta_{r,p,i}$
R_i		Correlated systematic	b_c		$\beta c_{,r,p,i}$


Input true values of variables
Input random and systematic uncertainties for each variable
Randomly generate an error along error distribution for each uncertainty source
Apply error to appropriate variables
Calculate result of value of interest from applicable data reduction equation
Calculate standard deviation of the value of interest
$P_{T,bm,1\text{-}8}$
P_{bar}
$P_{T,arr,1\text{-}7}$
Run simulation : i = 1 to M iterations
$b_{P_{T,bm}}$
$s_{P_{T,bm}}$
$\beta_{P_{T,bm,n}}(i)$
$\epsilon_{P_{T,bm,n}}(i)$
$P_{T,bm,n}(i) = P_{T,bm,n}(i) + \epsilon_{P_{T,bm,n}}(i) + \beta_{P_{T,bm,n}}(i)$
$b_{P_{bar}}$
$\beta_{P_{bar,n}}(i)$
$P_{bar}(i) = P_{bar}(i) + \beta_{P_{bar}}(i)$
$b_{P_{T,arr,unif}}$
$b_{P_{T,arr}}$
$s_{P_{T,arr}}$
$\beta_{P_{T,arr,unif,n}}(i)$
$\beta_{P_{T,arr,n}}(i)$
$\epsilon_{P_{T,arr,n}}(i)$
$P_{T,arr,n}(i) = P_{T,arr,n}(i) + \epsilon_{P_{T,arr,n}}(i) + \beta_{P_{T,arr,n}}(i) + \beta_{P_{T,arr,unif,n}}(i)$
$P_T(i) = f\,[\,P_{T,bm,1\text{-}8}(i),\ P_{bar}(i),\ P_{T,arr,1\text{-}7}(i)\,]$
NO
$i = M$?
YES
$u_{P_T} = \sqrt{\frac{1}{M-1}\sum_{i=1}^{M}(P_T(i) - \overline{P_T})}$
95% Expanded Uncertainty $= 2 * u_{P_T}$


Expanded (k=2)
Uncertainty in M_{ts}
96%
80%
64%
48%
32%
16%
0%
Variable 1
Variable 2
Variable 3
Variable 4
Variable 5


Systematic Uncertainty
Random Uncertainty
Percent Contribution to Uncertainty in Calculated M_{ts}
0
20
40
60
80
100
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
Nominal Mach Number


100
80
60
40
20
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
Nominal Mach Number
Percent Contribution to Uncertainty in M_{ts}
$b_{P_{T,cal}}$
$b_{P_{S,cal}}$
$b_{T_{T,cal}}$
b_{inst}


Percent Contribution to Uncertainty in M_{ts}
Nominal Mach Number
0
10
20
30
40
50
60
70
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
$s_{P_{T,bm}}$
$s_{P_{S,bal}}$
$s_{T_{T,bm}}$

Determining Potential Improvements

- Quantify the effects of:
  - Modifying calibration process
  - Increasing number of data points available for analysis
  - Improving instrumentation
  - Improving flow quality of facility
  - Modifying run time operations

➢ Perform cost-benefit analysis for effective facility and data improvement

Conclusions

- Thorough investigations of uncertainties in facilities at GRC underway
- Instrumentation level uncertainties will be easily identified using new spreadsheet tool, "MANTUS"
- Categorizing uncertainties as "random" and "systematic" useful in determining potential areas of improvement
- In-depth uncertainty analysis results and potential improvement scenarios provide keys to understanding how facilities and data can continue to improve